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Applications of Artificial Neural Networks in Friction Stir Welding: A Review

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Abstract-**This paper gives a review on the applications of artificial neural network in friction stir welding. Friction stir welding is a fairly new solid state joining process and has found numerous applications including in aerospace, marine, automotive, railway and many more. Artificial neural network (ANN) is a valued research area. Study has been done on mechanical properties of weldements.**

Keywords- Artificial Neural Network (ANN); FEM; Friction Stir Welding; Mechanical Properties; Welding; Friction.

I. INTRODUCTION

Friction stir welding (FSW) is a relatively new process for bonding metals. It was evolved by The Welding Institute of Cambridge, England in 1991.It was initially applied for aluminium alloys. FSW brings new innovations in the field of welding and had made noticeable development due to its ability to weld aluminium alloys which are considered unweldable by fusion welding technique. It is used to join similar and dissimilar alloys. Apart from aluminium and its alloys FSW can be used to join Cu alloys, Ti alloys, steel etc. The procedure of FSW is easy. It joins two surfaces using a non consumable tool and involves a complex process mechanics. It utilizes a non consumable rotating welding tool to generate frictional heat and plastic deformation at the welding location, there by affecting the formation of weld while material is in solid state. This technique is very environment friendly, efficient and versatile to provide satisfactory combination of microstructure and mechanical properties of weld. It is also known as green technology. The FSW being a solid state process offers numerous benefits when compared to other welding technique involving melting of material such as porosity, cracking etc. FSW process is associated with low temperature which results in low distortion and residual stress. FSW has many applications in various fields due to attractive properties of the process. It has wide importance in industries such as automotive, aerospace, maritime, food saving, fuel tank and many more. In the recent years several researches have been developed on FSW with the aim to fully highlight its mechanical and metallurgical characteristics.

Recently in the fields of material science and engineering, computer aided ANN modeling has gained importance [1].

ANN is a convoluted system composed of innumerable nerve cells. It is a computer system based on key understanding of configuration, composition, mechanism of human brain. With the help of rapid progress in computers and material science, material design can now be carried out based on the knowledge and experience of the fabricated materials [1].Using ANN the mechanical properties of the welded material can be determined giving welding parameters as input.It can be linked with Finite Element model to predict the final microstructure which in turn determines mechanical properties of welded metals. The FSW process involves complex non linear interactions between the welding tool and the material properties which are difficult to depict by analytical models so in such situations ANN can be easily explored and applied because of its capability to learn from examples like human beings.

II. FRICTION STIR WELDING PROCESS

FSW is an advanced welding process for bonding metals in solid state and uses a non consumable tool for this purpose. It is a solid state process which means coalescence takes place much below the melting point of the metals. The figure below shows the schematic of FSW welding process. It shows the materials joined in butt configuration.

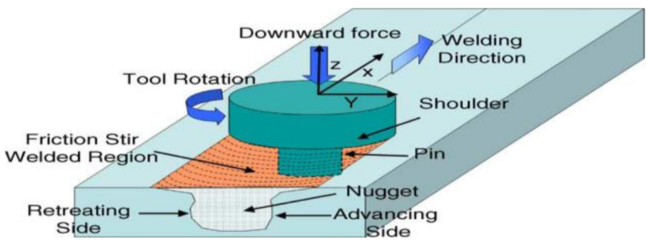

Figure 1. FSW Process[2]

The whole FSW operation consist of four stages-plunge, dwell, traverse & retraction. A cylindrical pin with large shoulder plunges into the workpiece up to a certain depth and then dwell for some time to let the workpiece temperature reach an optimal temperature and then traverses along the workpiece with a constant speed(welding speed) till the finish point and then retracts from the workpiece. A downward force provided by the tool is also necessary to maintain registered contact between tool and the workpiece.

The FSW involves complex interactions between the material and the tool.

The tool used in this process serves two important function-

- - Localized heating and material flow
- -Stir and move the material

The friction between the material & workpiece results in biggest component of heating and little comes from deformation of the materials. These heat inputs causes the material to soften without melting. The figure shows advancing and retreating sides. The advancing side is one in which welding direction and material flow are in same direction while it is in opposite direction in retreating side.

There are various controlling factor or welding parameters in FSW and they are as follows:

A. Tool rotation & Traverse speed

They are an important parameters in FSW and they are chosen with care for efficient welding. The relationship between the welding speeds and heat input is complex but it is observed that increasing the welding speed or decreasing the traverse speed increases the heat input and results in hotter weld and it is required for the plasticized flow of the material. But defects occur when the material is too cold or high heat input is applied.

B. Tool tilt & Plunge depth

A suitable tilt of the tool towards the trailing direction holds materials and holds the material efficiently from front to back of the pin. Plunge depth is the depth to which shoulder of the tool sinks into the material. The plunge depth needs to be correctly set to ensure downward force is achieved and tool penetrates the weld. When it is shallow the rotating shoulder cannot move the stirred material and when it is deep concave welds are produced causing thinning of welded plates.

C. Tool design

The tool is an important part of welding process to produce a good quality weld. It consists of a shoulder and the pin. As already mentioned the interaction between material and workpiece is the biggest component of heating while both the shoulder and pin affect the material flow. Pin shape plays a significant role in material flow and in turn controls the welding speed. The different pin profiles are:

- -Straight cylindrical
- - Tapered cylindrical
- -Threaded cylinder
- -Triangular
- -Square

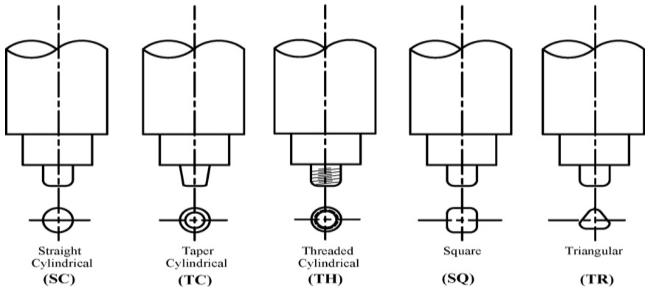

Figure 2. Pin Profile [3]

1) Straight Cylindrical

For the cylindrical pin, the rotation of the pin is symmetric in nature causing shear deformation of the material the pin surface.

2) Threaded Cylindrical

The threads on the pin significantly enhance plastic flow along the thickness direction immediately next to the pin the material driven by the threads moves downward from the upper sheet to the lower sheet, forming the major portion of the stir zone.

3) Triangular

Due to the asymmetric geometry of the triangular-shaped pin, successive rotation of the pin is believed to enhance the plastic flow of the material in the vicinity of the pin in the radial direction, compared to the cylindrical pin.

4) Square

Pin profiles with flat faces are associated with eccentricity. This eccentricity allows incompressible material to pass around the pin profile. Square pin profiled tool produces metallurgical defect free welds compared to other tool pin profiles. But produces mechanical sound. In addition, the triangular and square pin profiles produce a pulsating stirring action in the flowing material due to flat faces. There is no such pulsating action in the case of cylindrical, tapered and threaded pin profiles.

The FSW process results in asymmetric material flow due to complex reactions between weld tool and workpiece. It is broken into three parts as:

- Nugget Zone(Stir Zone)

This zone consist of highly deformed material and corresponds to the location of pin during welding.It is the zone where dynamic recrystallization occurs and the grains in this region are equiaxed and smaller than parent materials. This region is characterized by onion ring structure.

- Thermo mechanically Affected Zone

This zone occurs on either side of nugget zone. In this zone effect of welding parameters are lower than nugget zone although plastic deformation occurs in this zone but not recrystallization due to insufficient deformation.

- Heat Affected Zone

This is common in all welding process and is subjected to thermal cycles but not deformation. It retains the same grain structure as parent material.

Figure 3. A typical micrograph showing various microstructural zone in Friction stir processing 7075Al-T651(standard threaded pin, 400 rpm and 51 mm/min)[2]

III. ARTIFICIAL NEURAL NETWORK APPROACH

The evolution of artificial neural network (ANN) began approximately five decades ago and motivated by a desire to understand the brain and to emulate some of its strength. ANN approach adopts the brain metaphor, which indicates that intelligence emanate through a large no. of processing elements connected together, each performing simple operation. The long term knowledge base of neural network is encoded as a set of weights on connection between them. Due to this reason, the neural networks have been named as connectionist (Feldman and Ballard 1982). Neural networks consist of a knowledge base which is a computer program that acquires, represents and uses knowledge for a specific purpose and makes inference using that knowledge. The neural network acquires its knowledge through examples and then generalizes from a limited set of training data and predicts overall trend and functional relationships and there is no need to algorithmically converting an input to output as in analytical methods. ANN has intrinsic adaptability and work robustly even in noisy environment. It represents the knowledge in declarative manner and is invoked under certain inference strategy. In knowledge based systems ,knowledge is stored in knowledge base while control strategies are in separate inference engine so both are independent and can be updated when required. This approach revolutionizes the programming style and saves a lot of time and energy.

The basic unit in ANN is neuron. Neurons are connected to each other by links known as synapse and each synapse has an associated weight with it. Each neuron applies an activation function (usually non linear) to its net input (sum of weighted input signals) to determine its output signal. Learning in the neural network is associated with the adjustments of these weights. ANN system consists of three layers- input layer, hidden layer and output layer. Inputs from the input layer are processed in hidden layer and finally output vector is computed in output layer. A trained neural network can be thought of an expert in the category of information it has been given to analyze. This expert can be used to provide projections (can be tested) given new situations of interest. An ANN is characterized by (1) architecture i.e. its pattern of connection between neurons;(2)its method of determining weights on the correction i.e. its training or learning algorithm;(3)its activation function.

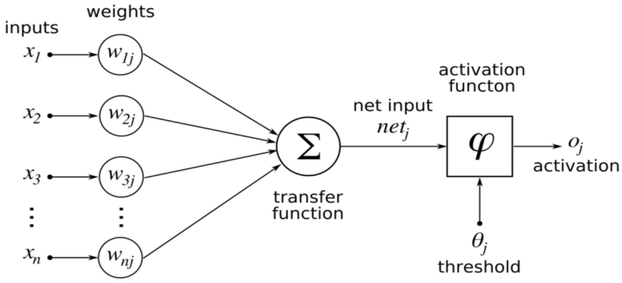

Figure 4. ANN Model [4]

Acccording to the interconnection scheme a network can be feed forward network is one in which all connections point in same direction (from the input layer towards the output layer). A recurrent network is one in which there are feedback connections or loops. In ANN providing adequate training to the network is important. The network should neither be under trained nor over trained. The training or learning in neural networks is of two types-supervised and unsupervised. Supervised learning is one in which outputs are known and when input is applied ANN process the input and gives output which is compared with actual input where as unsupervised learning follows unlabelled instances.

There are many learning algorithms available for ANN and one such algorithm is backpropogation algorithm. In current review work this is mostly used. The backpropogation network is a multilayer feedforward network and the learning rule is a kind of gradient descent technique with backward error (gradient) propogation. It consist of repeated applications of following two techniques-

Forward pass: The network is triggered on one example and error between the actual output and preferred output is computed.

Backward pass: The network error is used for updating the weights. The error passes on backwards from output layer through the network layer by layer. This is done by recursively computing the local gradient of each neuron.

The backpropogation algorithm consist of following stages:[5,6]

(1)Weight initialization: Set all the weights to small random numbers;

(2) Calculation of activation: It depends on the instance presented to the network. The activation level O_j of a hidden and output unit is determined by

$O_j = F(\sum W_{ji}\, O_i - \theta_j$ where W_j is the weight from an input O_i , θ_j is the node threshold, and F is a sigmoid function.

$$F(a) = \frac{1}{1+e^{-a}}$$

(3) Weight Training:(i)Start at the output units and work backwards to the hidden layers recursively. Adjust weights by-

$W_{ji}(t+1) = W_{ji}(t) + \boldsymbol{\Delta}\, W_{ji}$ where $W_{ji}(t)$ is the weight from unit i to j at time t(or *t*th iteration) and ΔW_{ji} is the weight adjustment.

(ii)The weight change is computed by:

$\Delta W_{ji} = \eta \delta_j O_i$ where η is the trial independent learning rate(0<η<1) and δ_j is the error gradient at unit j. Convergence is sometimes faster by adding momentum terms:

$W_{ji}(t+1) = W_{ji}(t) + \eta \delta_j O_i + \alpha[W_{ji}(t) - W_{ji}(t-1)]$ where 0<α<1.

(iii)The error gradient is given by:

-For the output units:

$\delta_j = O_j(1-O_j)(T_j - O_j)$ where T_j is the desired(target) output activation and O_j is the actual output activation at output unit j.

-For the hidden units:

$\delta_j = O_j(1-O_j)\sum_k \delta_k W_j$ where δ_k is the error gradient at unit k to which connection points from hidden unit j.

(4) Repeat iterations in terms until convergence in terms of the selected error criterion. An iteration includes presenting an instance, calculating activations, modifying weights.

Below is the conclusion reviews of different papers

Artificial neural network model is developed by different researcher for analysis and simulation of the relationship between friction stir welding parameters of materials and its mechanical properties. The welding parameters such as weld speed and tool rotation speed are inputs for the model and mechanical properties such as yield strength, tensile strength, elongation, and hardness are outputs.

The experiments are conducted using different combinations of weld speed and tool rotation speed called patterns and results are obtained and those results are used to train the artificial neural networks. Some patterns are used for training the network and some are used for testing the network.

In many research papers feed forward neural network with back propogation algorithm is employed in which error is propogated backward and is minimized. In most models MATLAB software is used for training and testing the network. Then a comparison is made between the experimental results and that obtained using artificial neural network.

Okuyucu,et.al[7] devloped and analysed the performance of artificial neural network model and characteristics of friction stir welded aluminium plates on the basis of welding parameters. It is observed that increase in welding speed increases tensile strength and increase in tool rotation speed (TRS) decreases tensile strength. Hardness of the weld metal has been found lower than in heat affected zone (HAZ).It is also observed that ANN shows good result.

Shojaeefard, et al.[8] also observed microstructure and mechanical properties of the Friction stir welding (FSW) of AA7075-AA5083-O aluminium alloys and vary the welding parameters to obtain optimal quality characteristics. An artificial neural network (ANN) was developed for establishing the relation between FSW parameters and mechanical properties. The hardness and tensile properties of the material was evaluated. The performance of ANN was in good agreement with experimental data. The particle swarm algorithm was used for solving multi objective optimization problem using Pareto-optimal non dominated set and then using technique for order preference by similarity to ideal solution (TOPSIS). Friction stir welding is widely used for joining dissimilar alloys. The results are enhanced by careful judgment w.r.t material placement and process parameters, depending on properties of materials to be joined. The friction stir welds are obtained at various combinations of weld speed and tool rotational speed (TRS). Both the weld speed and TRS should not be too low or too high and a compromise should be made between the two. Feed forward neural network with backpropogation algorithm was employed. Feed forward is a neural network in which output of each neuron is connected to the next. ANN consist of input layer, hidden layer and output layer. The input parameters were weld speed and TRS and output consist of hardness and tensile shear force. Matlab software is used as running platform in ANN.

Using ANN it is also possible to predict input parameters when ultimate tensile strength is given as input. Chiteka[9] devloped it. The alloys AA6061 and AA7075 were used for this purpose. Intially an ANN model is developed for determining UTS and then reverse prediction is done. The network is trained using Levenberg-Marquardt training algorithm. However input parameter prediction is quite complex because there are several combinations of input parameters that can yield same UTS and at the same time predicted input parameters may not be available on the machine.

Like aluminium titanium is also considered un weldable by traditional fusion welding methods and so FSW is a promising solution for titanium also. The concept of ANN are also applied for microstructural and mechanical performances of friction stir welded dual phase Ti-6Al-4V titanium alloy[10]. This titanium alloy consist of α+β phase. During experiment parameters are selected in such a way to obtain different temperature in the stir zone which will result in different microstructure. This model was linked with FEM model of the process to utilize main field variables as input. Two ANN model were developed one for microhardness and the other for microstructure. The input of the ANN model – temperature,strain & strain rate was taken from FEM model. It was observed that in the stir zone of FSW joint the microhardness is higher than base metal which is the biggest difference from aluminium alloys in which microhardness in stir zone is less than parent material.

The neural network can also be used in determining the average grain size in friction stir welding process[11]. The grain size depends on the material flow occurring in FSW process which in turn depends on welding parameters i.e tool rotation speed and welding speed. The finite element model (FEM) is developed to give local information on field variables such as temperature(T),strain, strain rate, Zener-Holloman parameter which gives the non linear effect of temperature into strain rate. A multilayer feed forward neural network based on backpropogation algorithm was developed taking inputs from FEM model and output as grain size of

material. The network is trained on butt joints and then tested on further lap and T joints. A good agreement was made between the neural network prediction and experimental value. In nutshell, the use of ANN and FEM link the process parameters to final grain size which in turn strongly deternines the joint resistance.

FSW although is a widely used method and is used to weld materials which are difficult to weld by conventional methods but setting of system parameters in FSW is very important. Improper setting of welding parameters gives weld with undesirable defects. Boldsaikhan, et.al[12] presents an intelligent algorithm for detecting wormhole defects in friction stir welding in non destructive manner using a Neural Network model along with discrete Fourier transform in real time. Good accuracy is achieved with no bad weld characterized as good weld.

The feedback forces provided by friction stir welding process is evaluated. The feedback forces are the resistances induced by plasticized material in response to weld tool material. The oscillations of the feedback process are related to the dynamics of material flow so the frequency spectra of feedback process are used for detecting wormhole defects. The wormhole defect is the presence of cavity below the weld surface. It arises due improper setting of parameters during friction stir welding. A neural network with one hidden layer trained with back propogation algorithm is used for classifying frequency patterns of feedback forces into good and bad weld. The discrete fourier transform is used for obtaining the frequency patterns. The good weld is classified as weld which has stable spindle frequency (weld tool's rotation speed) oscillations in feedback forces data. The real time algorithms proposed consist of:

1) *Extracting a feature vector from lower portion of frequency spectrum because significant information lie in lower portion.*
2) *Employing a feed forward neural network with back propagation algorithm. The advantages of defining the problem empirically rather than analytically.*

Hence in nutshell we can say that the above algorithm not only detects wormhole defects in real time it gives information about the quality of the friction stir weld by evaluating non linear oscillations of feedback forces.

Angular distortions due to butt welding of plates is also one of the major problem encountered in industry. So projection of distortion prior to welding is valuable. Choobi ,et al.[13] revealed welding induced angular distortion prior to welding in single pass butt welded 304 stainless steel using artificial neural network (ANN). A multilayer feedforward back propogation neural network was designed using MATLAB. The input to the neural network was given by a series of finite element simulation for a wide range of plate dimension. To validate the results of numerical simulation a series of experiments have been performed and temperature histories and numerical simulations have been measured for two different cases. The ANN model was able to predict accurately welding induced angular distortions. 3D finite element simulation of welding process has been performed by by the uncoupled analysis using ANSYS 1.0. The input of the neural network were plate length(L) and width(W) and output were deflection of the plate at weld start edge, at mid section of the plate and at weld stop edge.

IV. CONCLUSION

This paper reviews the applications of ANN in FSW and the FSW process it can be concluded that ANN results are in good agreement with the experimental results and ANN can be used to predict outputs for inputs they have never been experienced.

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